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Adaptation in a Himalayan Water Resources System under a Sustainable Socio-Economic Pathway in a High-Emission Context

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Abstract:

Climate change in the Indian Himalayan region is being manifested in loss of glaciers and altered patterns of monsoon rainfall. Simultaneously, rapid population growth together with economic development are increasing sectoral water demands and changing land use patterns. This study investigated the impact of this complex interplay on water resources in the Beas-Sutlej water resources system. The GFDL-CM3 model was used to describe RCP8.5 future meteorological conditions throughout the 21st century. Population and land use changes were projected under the Shared Socioeconomic Pathway-1 (SSP1). The Water Evaluation And Planning (WEAP) system was applied for assessing sectoral water demands. The results showed increasing runoff during the pre-monsoon and monsoon seasons, due respectively to increased glaciers melting and more rainfall. It also emerged that irrigation water demand will decrease moderately in Punjab (8 - 13%) and Haryana (1 - 9%); however, the situation was reversed in Rajasthan where it increased by 14%. Adaptation strategies were proposed including increased water allocation to Rajasthan and converting lands to cultivating more staple crops in Punjab and Haryana. **Keywords:** Climate change; socio-economic change; irrigation water demand; adaptation strategies; WEAP

Introduction

The greater Himalayan region is known as the largest area covered by glaciers and permafrost outside the polar region (Eriksson et al. 2009). This area is currently supplying freshwater resources to more than 1.5 billion people across South Asia and it is estimated that, in India alone, 900 million people are relying on its water resources for agriculture, domestic, and industrial uses (NRC 2012; Raveendranathan 2017). However, evidence in the last few decades have confirmed that most glaciers in the Himalayan region are retreating rapidly due to global warming (Bolch et al. 2012; Kulkarni and Karyakarte 2014; Smadja et al. 2015). Du et al. (2004) showed that average temperature in the Himalaya has increased by 0.74°C in the last 100 years, and more significant rise are projected for the end of the Century between 2.36°C to 5.51°C (Chaturvedi et al. 2014). Nepal and Shrestha (2015) also argued that the future temperature in the upper Indus, Ganges, and Brahmaputra basins is likely to increase with greater warming in the Indus Basin during winter. Increasing temperatures is thought likely to result in drastic glacier losses (Dyurgerov and Meier 2004; Kulkarni and Karyakarte 2014) which, in the northern region of India where glacier and seasonal snow melt currently contributes about 70% of the runoff to the Indus, Ganges, and Kabul rivers (Barnett et al. 2005; Kattelmann 1987; Lutz et al. 2016), can have devastating consequences for the region's hydrology and all those depending on it for various purposes (water supply, irrigation, hydropower generation, etc.).

The simultaneous effects of rapid population and socio-economic growth, coupled with changed in surface and groundwater availability patterns, and inefficiencies in water use practices have caused demand for water in India to increase noticeably in recent years. For example, the Indian population has grown from 1.05 billion to 1.234 billion between 2000 and 2010 (MHA 2011) and according to Goyal and Surampalli (2018), 1.2 billion of Indian population have experienced tremendous economic growth in the last 20 years with only 4%

and 9% of the world's water resources and arable land, respectively. Garg and Hassan (2007) concluded that the water scarcity in India will be severe based on the projected annual unmet water demand in 2050 of 229 BCM (billion cubic meter) for optimistic scenario and 396 BCM (pessimistic scenario) even after full development of utilizable water resources, as a direct consequence of its large population. For these reasons, it is vital to understand the current water situation in the Indian Himalayas as an ingredient for developing adaptation plans for coping effectively with future water-related challenges.

Modelling studies about the impacts of climate change are abundant across the Himalayas with few recent ones also incorporating the effects of socio-economic changes such as water supply requirements and water infrastructures operation. Momblanch et al. (2019) combined the effects of climate change with several socio-economic assumptions for understanding water-food-energy-environment nexus in the Himalayas, without taking into account land use change aspect. The study showed that socio-economic impacts on nexus components are much greater than climate change. Besides, some other studies have considered land use change impacts alone on Himalayan hydrology or along with climate change while others have been limited to climate change impacts only. For example, Adeloye and Dau (2019) assessed the impacts of climate change on the reservoir systems in the Beas basin and found that climate change induced reduction in runoff will cause deterioration in reservoir vulnerability and reliability. Ashraf (2013) studied the effects of socio-economic change on hydrological system in the Himalayan watershed. The study suggested that changes in land use in recent years have brought significant impacts on water flows, sediments and threat to eco-hydrology.

From the foregoing, it is clear that no study has yet analysed the combined effect of all these changes on water security as far as we are aware. The current study represents a radical departure by its recognition of climate, population and their complex interactions with land and water infrastructure systems as the main factors driving the balance between water availability and demand. It applies a system modelling approach to integrate hydrologic and socio-economic aspects in the baseline and uses the delta change method (climate) and Markov chain analysis (land use) to project them into the future. The methodology is applied to the Beas-Sutlej water resources system in the western Himalayas in India. The outcomes of the impact analysis are used to design and evaluate adaptation measures to address future challenges related to water use. The outcomes of this study are expected to be useful for the Bhakra and Beas Management Board (BBMB) which has responsibility for the management of the main infrastructures in the Beas-Sutlej system to supply water to the Indian States of Punjab, Haryana and Rajasthan majorly for irrigation.

Study Area

The Beas-Sutlej water resource system is located in the northern region of India (Figure 1). The system has a total area of 76,400 km^2, of which 34,100 km^2 in the Himachal Pradesh and Punjab, and 42,300 km^2 is in the Tibet Autonomous region, China (Momblanch et al. 2019). There are two main water regulation infrastructures in the basin – the Pong dam on the Beas River and Bhakra dam on the Sutlej – whose associated reservoirs serve large scale irrigation projects (or Command Areas) in the downstream States of Punjab, Haryana and Rajasthan, generate hydro-electric power and provide flood relief (Adeloye et al. 2019). Table 1 summaries the gross water requirements at the command areas estimated by multiplying land area under each crop with water requirements of the crop per unit of area. Located at the foothills of the Himalayas, both reservoirs benefit from significant meltwater contribution, i.e. 59% of runoff in Bhakra and 35% in Pandoh Dam annually (Kumar et al. 2007).

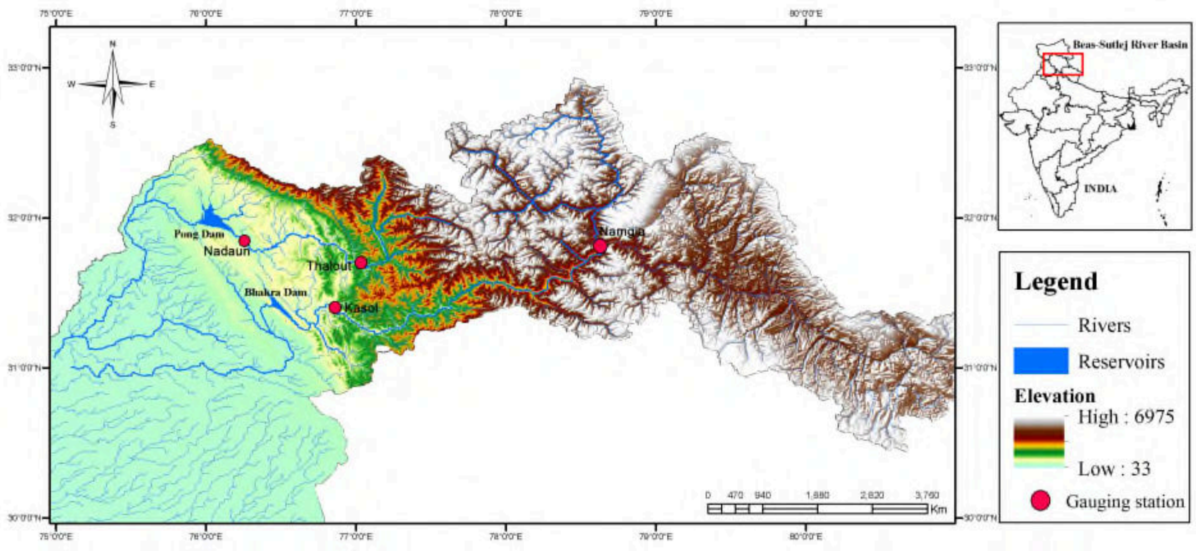

Figure 1.

Most precipitation falls as rainfall during the monsoon season between July and late September; however, there is a significant precipitation input as snowfall in winter brought by the westerly disturbances (Bannister et al. 2019). The average annual rainfall is about 1,800 mm at the Beas catchment and 1,200 mm at the Sutlej catchment. Mean annual temperature varies between -10°C and 10°C depending on the altitude. Land use mainly consists of irrigated land and population centres situated in the plain areas of the basin's downstream, while forest is in the foothills and permanent snow/glaciers is in the highest elevation – upstream of the Himalayas. The population are mainly distributed in the cities of Ludhiana (1.6 million persons), Amritsar (1.18 million persons), Chandigarh (1.05 million persons), Jalandhar (0.87 million persons), and Patiala (0.4 million persons) as recorded in 2011 (MHA 2011).

In India, the standard norm for domestic water consumption is 40 *lpcd* (liters per capita per day) for rural areas and 135 *lpcd* in urban areas (WaterAid 2005), except at Delhi for which the per capita water consumption is 225 *lpcd* (according to BBMB); New Delhi receives a part of its drinking water supply from the two reservoirs. The per capita demand figures were used to arrive at the water demand shown in Table 1. As seen in the Table, the drinking water requirements in the basin are much lower than the irrigation water demand; it is therefore unlikely that domestic water impacts are going to be as significant as the land use change and associated irrigation water impacts.

According to the Central Statistics Office (MOSPI 2018), the hydropower energy contribution to the energy mix in Punjab, Haryana, and Rajasthan in 2017 accounts for 14.8%, 29.2%, and 0.4% respectively of the total energy production. In addition, the average per capita energy consumption between 2008 and 2015 is 1,762 kWh in Punjab, 1,653 kWh in Haryana, and 951 kWh in Rajasthan. The demand from hydropower based on the current level of contribution is an estimated 15.8 billion kWh, which is slightly less than the total hydropower generation of 16.5 billion kWh in the Sutlej-Beas system to which the two large reservoirs, the Pong and Bhakra, contribute the largest share. Thus, the hydropower generation might be sufficient based on existing conditions but the situation might change in the future based on the situation of the hydrologic, climatic and socio-economic drivers.

Methodology

For understanding the effects of climate and socio-economic changes on water resources systems in the Beas-Sutlej river basin, future water demand under assumptions of the Representative Concentration Pathway (RCP) 8.5 and Shared-Socioeconomic Pathway (SSP) 1 was considered. The high emission RCP8.5 was chosen because it represents business as usual and thus very likely to represent the pathway for most of India as the country embarks on its extensive industrialisation agenda aimed at lifting its population out of poverty. The adoption of SSP1, a world of sustainability-focused growth and equality, although at odds with the high energy use envisioned by RCP8.5 is nonetheless compatible with the poverty-reduction agenda of the Indian government. SSP1 would be a reasonable assumption for the country without a global climate policy.

Data sources

The meteorological data used for the historical period (i.e. baseline: 1990-2007) was generated using the Weather Research Forecasting (WRF) model at a 5 km x 5 km resolution (Bannister et al. 2019). For future climate projections, outputs from a coupled climate model developed at the NOAA Geophysical Fluid Dynamics Laboratory Climate Model version 3 (GFDL-CM3) was downloaded from the KNMI Climate Explorer (Trouet and Van Oldenborgh 2013) for the middle (2033-2050) and end (2083-2100) of the century. Measured monthly river discharge data for 1990 - 2007 were available at four sites – Thalout and Nadaun in the Beas River, and Namgia and Kasol in the Sutlej from the BBMB.

Land cover maps at 300 m spatial resolution provided by the European Space Agency Climate Change Initiative (ESA-CCI) for the years of 2000, 2005, and 2010 were used for describing the spatial variability of vegetation and land use (UCLouvain 2017). Soil type map given by the Land and Water Development Division – FAO (Vargas 2007) was also used to determine soil moisture conditions for irrigation lands. Other physical datasets such as elevation, slope, roads, and river were reanalysed using the ASTER Global Digital Elevation Model (USGS 2018) data at 30 m resolution.

Population in the baseline was obtained from the Census of India of 2000 (MHA 2011) and the future projections in 10-year intervals from 2010 to 2100 were obtained from the Climate and Global Dynamics Laboratory for the SSP1 scenario (CGD 2020). The data are in 1-km grid cells as re-downscaled by Gao (2017). The projected population data were used for quantifying future domestic water consumptions similarly to the baseline consumption reported in Table 1 but considering SSP1 population projections.

Downscaling climate model with the Delta Change approach

GFDL-CM3 projected precipitation and temperature data under RCP 8.5 were downscaled using the Delta Change approach proposed by Lenderink et al. (2007).

The monthly time series of historical (1990 – 2008) and future simulated outputs of GFDL-CM3 for each future time slice, i.e. mid-century (2033 – 2050) and end-century (2083 – 2100), were used to calculate time series of delta changes, which were then averaged to obtain monthly delta changes (ΔP_m^{GFDL} and ΔT_m^{GFDL}). The resulting monthly Δ values were applied to the high-resolution climate WRF and RegCM4 baselines in the hills and the plains respectively ($P_{m,y}^{B^{HighRes}}$ and $T_{m,y}^{B^{HighRes}}$) to provide the corresponding high-resolution future climate projection as given below:

$$P_{m,y}^{F^{HighRes}} = P_{m,y}^{B^{HighRes}} \times \Delta P_m^{GFDL} \quad (1a)$$

$$T_{m,y}^{F^{HighRes}} = T_{m,y}^{B^{HighRes}} + \Delta T_m^{GFDL} \quad (1b)$$

where, P is precipitation, T is temperature, F refers to a future time slice, B refers to the baseline period, *m* and *y* are month and year, respectively

Our choice of the delta approach stems from the fact that it is simple and is widely used in hydrological impact studies. By using monthly change factors, the method accounts for any simulated changes in the periodic patterns within the GFDL-CM3 simulation, in particular in the timing and strength of the monsoon and westerly disturbances which shape the hydrology in the study area. A further key benefit of the Delta change method is its elimination of large discrepancies between the absolute values of baseline and projected climate. However, while it adjusts the mean of the time series, other important statistics such as the standard deviation, wet frequencies, intensity, number of rainy days remain largely unaffected (Mendez et al., 2020; Bergstrom et al., 2012).

Projected land use change with Markov Chain analysis

Markov Chain analysis is a dynamic process based on Markovian random process, which has been used extensively for projecting land cover change (Fathizad et al. 2015; Gibson et al. 2018). The method requires the transition probability matrix to describe a probability of land cover changes from one period to another (Eq. 2a). Once the transition probability matrix is known, then projection for land use in the next state is estimated using Eq. 2b (Hamad et al. 2018; Liping et al. 2018; Marko et al. 2016):

$$\tau = \begin{vmatrix} \tau_{11} & \tau_{12} & \cdots & \tau_{1n} \\ \tau_{21} & \tau_{22} & \cdots & \tau_{2n} \\ \cdots & \cdots & \cdots & \cdots \\ \tau_{n1} & \tau_{n2} & \cdots & \tau_{nn} \end{vmatrix} \qquad \begin{matrix} \sum_{j=1}^{n} \tau_{ij}=1 \text{ ; } i,j = 1,2,\ldots n \\ 0 \leq \tau_{ij} \leq 1 \end{matrix} \tag{2a}$$

$$S_{(t+1)} = \tau \times S_t \tag{2b}$$

where, τ is the transition probability matrix; τ_{ij} represents the probability of the system transitioning from land use type *i* to *j*; *n* is the total number of land use types; and S_t and S_{t+1} are land use maps at time *t*, and *t+1*.

The main task for the land use cover change projections, therefore, is the determination of the transition probability matrix. One popular approach is to model the relationship between land use patterns and those factors that have been known to influence them. For example, it has been noted that land use is dependent on various explanatory variables such as elevation, slope, distance to urban, rivers, roads, population, and Gross Domestic Product (GDP), which can serve as factors for explaining how potential transition of land use change respond to socio-economic changes. Given that the relationship may be complex and difficult to express in closed mathematical forms, a data-driven, multi-layer perceptron artificial neural network (MLP-ANN) (Park and Lek 2016; Walczak and Cerpa 2003) was used to model the relation between the explanatory variables as inputs and the transition probabilities as output.

The MLP is a feed-forward network approach that computes the output from multiple real valued inputs by forming a linear combination according to its input weights associated with an activation function. In the neural network architecture, explanatory variables form the nodes (or neurons) in the input layer, land change pattern maps between 2000 and 2005 were analysed to determine the observed potential transition probability that form the nodes in the output layer. Between the input and output layer is a single hidden layer that improves the modelling of the intrinsic non-linear relationship in the data. The ANN requires training to determine the best weights and the number of nodes or neurons in the hidden layer. The study used 50% of sample size (pixels of map) for training and the rest 50% for testing. The best number of hidden layer nodes was determined to be 7 using the traditional trial and error approach. Performance of the network was assessed using the Root Mean Square Error (RMSE) and R^2 indices.

Once trained and validated, the resulting model can be used to obtain the transition probabilities for future time-slices once projections of the explanatory variables are known. The Markov Chain will then use these transition probabilities derived from the MLP and the historical land use pattern to project the land used pattern for the future (see Eq. 2b). As noted earlier, land cover maps for the years 2000 and 2005 were used for the training and testing and that for 2010 was used for validation.

For validating the complete land use pattern map model, the Kappa statistics were used for assessing the agreement between two categorical images, where each cell in maps has a multinomial distribution among any number of categories. In this study, it was used to compare the agreements between historical and predicted land use maps in 2010. Details of the Kappa statistics are available elsewhere e.g. (Monserud and Leemans 1992; Pontius 2000; Pontius 2002). In standardization, Kappa index of agreement is calculated using Eq. 3a. Since agreement in cells of compared maps use the information of location and quantity, alternative statistics have been lately explored for further performance evaluation including (Pontius 2000): K_{no} – measures the agreement in cells without location and quantity information (see Eq. 3b); $K_{location}$ – measures the agreement in cells for location (see Eq. 3c); and $K_{quantity}$ – measures the agreement in cells for quantity (see Eq. 3d). According to Landis and Koch (1977), Kappa values greater than approximately 0.75 indicate very good to excellent agreement, values between 0.4 and 0.75 indicate fair to good agreement, and values of 0.4 or less indicate poor agreement.

$$K_{standard} = \frac{(P_0 - P_c)}{(P_p - P_c)} \tag{3a}$$

$$K_{no} = \frac{(P_0 - P_{no})}{(P_p - P_{no})} \tag{3b}$$

$$K_{location} = \frac{(P_0 - P_c)}{(P_l - P_c)} \tag{3c}$$

$$K_{quantity} = \frac{(P_0 - P_c)}{(P_q - P_c)} \tag{3d}$$

In the above, P_0 is the observed proportion of correct classification that has been simulated by the model; P_c is the proportion of P_0 that has occurred due to chance or false alarm (i.e. not reality and so the better the simulation, the lower is the value of P_c); P_p is the proportion correct when classification is perfect for both location and quantity ($P_p = 1$); P_{no} is the proportion correct without information of location and quantity; P_l is the expected proportion correct due to chance for location; P_q is the proportion correct due to chance for quantity.

WEAP model

The Water Evaluation and Planning system (WEAP) developed by the Stockholm Environment Institute (Sieber and Purkey 2011) has been widely used worldwide in many regional water allocation problems, e.g. (Dau et al. 2020; Dau et al. 2018; Kou et al. 2018;

Momblanch et al. 2019). The model aims at supporting integrated water resources planning and management by representing the water allocations between agricultural, municipal and environment uses, which usually requires a full integration of supply, demand, water quality, and ecological considerations. WEAP uses a network flow approach solved with linear programming to determine water production, storage and consumption in nodes (i.e. catchments, reservoirs/aquifers and water demands, respectively) and water movement through arches which represent rivers, diversions and transfers, based on user-defined supply priorities. More details on the rainfall-runoff modelling and other features of WEAP are available elsewhere (Dehghanipour et al. 2019; Rajeevan and Mishra 2020; Sridharan et al. 2019).

The model of the Sutlej-Beas system used in this study has been developed at Cranfield University as part of SusHi-Wat (https://www.egis.hw.ac.uk/sushiwat), an international collaborative research on the Indian Himalayas, and has been published elsewhere (Momblanch et al. 2020). The mountain hydrology is represented using the Rainfall-Runoff Soil Moisture Method (SMM) in WEAP in a semi-lumped fashion, considering 23 sub-catchments and 600 m elevation bands which result in 165 spatial elements (i.e. catchment nodes). Each spatial element has distinctive input data, which allows representing the spatial variability in the study area and that can be modified to represent different scenarios. The gridded climate data from the regional climate models were spatially aggregated by catchment node in their respective regions (WRF for the hills and RegCM4 for the plains) for the baseline. Similarly, the delta changes were applied to each catchment node to represent climate change. Each catchment also has its distinctive land use classes and soils, which have different hydrological behaviours. The projected land use change is reflected in the model by modifying the area that each land cover class represents in a catchment, thereby, modifying its hydrological behaviour.

The SMM uses a temperature-index model to track snow and glacier accumulation and melt. Glaciers in each sub-catchment were considered as separate catchment nodes with area and average initial depth based on detailed studies (unpublished for the baseline, and published by Prasad et al. (2019) for the climate change scenario). For the purposes of the mass balance, accumulation for glacier depth is considered as uniform. The glaciers volume is then calculated by multiplying the ice depth with the sub catchment area containing of snow and ice (as tracked by the temperature-index modelling).

Domestic water demands (water demand nodes) have been characterised with a per-capita consumption of the rural and urban population in each district within the study area. The projected changes in population, which drive changes in domestic water demands, were used. The non-consumptive use of water for hydropower generation was limited to plants with generation capacity above 100 MW based on their design characteristics, i.e. hydraulic head, turbine capacity and plant factor.

Irrigation water demand in WEAP is represented as the water supply requirements in the command (or irrigated) areas in the States of Punjab, Haryana and Rajasthan and is estimated using the MABIA method. Each command area is considered as a lumped element with a specific cropping pattern and irrigation schedule as provided by local stakeholders. MABIA uses the "dual K_c" method (Allan et al. 1998) to scale the actual evapotranspiration (ET_c) from the reference crop evapotranspiration (ET_o). By "dual", it means that the K_c is divided into two components, namely the "basal" crop coefficient (K_{cb}) and the soil evaporation coefficient (K_e). The basal crop coefficient is the ratio of the crop evapotranspiration to reference evapotranspiration (ET_c/ET_0), when topsoil is very dry that direct evaporation is almost nil but water is present from the root zones to the crops for transpiration to continue (Allan et al. 1998). As the soil becomes wetter or close to saturation following rainfall or irrigation, evaporation dominates the evapotranspiration process and the value of K_e increases. In reality at most times, both K_{cb} and K_e will be operational and the scaled ET_c becomes:

$$ET_c = (K_{cb} + K_e)ET_0 \tag{4}$$

Algorithms for estimating K_{cb} and K_e for different growth stages of crops are provided by Allan et al. (1998).

The crop characteristics considered in the Sutlej-Beas model are the ones provided in the WEAP crop library, specifically for crops in the study region (i.e. North India) or nearby (Pakistan). The main infrastructures for the water management and supply in the system, i.e. Bhakra and Pong reservoirs, the Dehar transfer from the Beas to Sutlej River, and the main canals in the command area were also included in the model (Figure 2). The model has been calibrated and validated using observed river discharges at four gauging stations and the stored volumes in Pong and Bhakra reservoirs, using manual calibration and considering Nash-Sutcliffe Efficiency, Pearson's correlation coefficient and Percent bias as performance indicators as reported in Table 2.

Evaluation of performance of the Beas-Sutlej system reservoirs

For evaluating the performance of the Pong and Bhakra reservoirs in meeting the various demands from their allocations, time-reliability (R_t), volume-reliability (R_v), resilience (φ), and vulnerability (η) indies were used (Adeloye and Dau 2019). The time reliability is the ratio of the number of occasions the demand (irrigation, domestic or hydropower) was fully met to the total number of periods in the simulation. The volumetric reliability is similar to the time reliability but instead of counting the time periods, the actual volume of water supplied is viewed against the actual demand in each period. Given that the time domain reliability fails to take into account the severity of water shortage, the volumetric reliability is usually higher than the time reliability for any given water resources system. The resilience measures the likelihood of a reservoir recovering from a failed state, where a failed state occurs when release is less than demand. Finally, the vulnerability is a measure of the impact of water shortage and is usually estimated as the mean of the maximum water shortage occurring across the series of water shortage sequences in the simulation.

$$R_t = \frac{N_s}{N};\ 0 < R_t \leq 1 \tag{5a}$$

$$R_v = 1 - \frac{\sum_{t=1}^{N}(D_t - D'_t)}{\sum_{i=1}^{N} D_t};\ (0 < R_v \leq 1) \tag{5b}$$

$$\varphi = \frac{f_s}{f_d};\quad f_d \neq 0 \tag{5c}$$

$$\eta = \frac{\sum_{t=1}^{f_d}[(D_t - D'_t)/D_t]}{f_d};\ t \in f_d \tag{5d}$$

where, N_s is total number of months out of *N* month that demand was met; f_s and f_d is number of continuous sequences of failure periods and the total duration of the failures, respectively; D_t and D'_t are demand and actual supply during time *t*, respectively. All the indices in Eqs. 5a-d are dimensionless ranging from 0 – 1. Except for the vulnerability, zero represents non-performance while 1 is perfect (no-failure) performance. The reverse is the case for the vulnerability.

The use of these indices for reservoir assessment is not without its problem, principally because of the discordance in their indications. This was why Adeloye et al. (2017) attempted to rationalise the two reliability measures, i.e. the time-based and volume-based, and by so doing to eliminate the discordance. Campos et al. (2014) considered a threshold of 90% as being a satisfactory performance for meeting water demands and this threshold can be adopted for the two reliability indices and the resilience. As for the vulnerability, the classification proposed by Goharian et al. (2016) has often been adopted (see Basto et al., 2020), i.e. low (0

– 10.5%); medium (10.6% – 15.3%); medium-high (15.4% – 23.7%); high (23.8% – 29.1%); medium-extreme (29.2% – 33.20%); and extreme (33.3% – 40.2%).

Impacts on future sectoral water allocation and demand

The impacts of the above changes in the drivers of water availability in the basin were tested by using them to force the calibrated and validated WEAP model. The objective here is not to test the relative significance of one driver over the other but to assess their integrated effect. This is useful as these changes are unlikely to occur independently but in combination. Our approach will thus provide the robust balance between water availability and potential of future water demands required for developing effective adaptation measures for tackling water-related problems.

Results and Discussions

Climate change hydrological impact assessment with Delta Change approach

As mentioned previously, the future climate change projected by the GFDL-CM3 model under RCP8.5 was downscaled using the delta method. Despite the recent growing trend of using ensembles approach for climate change impacts assessment in order to accommodate the between-GCM variability in projected climate, the use of single GCM model (GFDL-CM3) for this assessment can be justified on the basis that it represents an extreme future climate scenario with the highest temperature increase in the Himalayan region (Prasad et al, 2019).

The results of the delta-change climate impacts are summarised in Figure 3. While the mean annual precipitation will decrease by 3% in the mid-century and increase by 5% in the end-century in comparison to the baseline period, there are very significant variations in the seasonal amounts as shown in Figure 3a. In general, precipitation will significantly increase in the monsoon season but will decrease in other seasons. The decrease in the post-monsoon planting seasons in some of the states will be a major worry because the need for increased irrigation water from the reservoirs may be threatened. The average annual temperature shown in Figure 3b shows that it increases consistently during the century by about 2.4ºC to 5.0ºC in comparison to the baseline period. Increase in the temperature will affect the crop water requirements (evapotranspiration), the direct loss by evaporation of the stored water in the reservoirs and the contribution of melt snow and glaciers to the runoff.

Despite the large projected increase in precipitation during summer monsoon season, the increases in inflows to the Pong and Bhakra reservoirs are moderate. For example, the WEAP simulation shows that the mean annual runoff (MAR) for the Pong reservoir is 6,241 MCM (Million Cubic Meters) for the baseline (1990 – 2007), this is projected to increase to 6,638 MCM in the mid-century and 6,812 MCM in the end-century, a maximum change of 9%. At the Bhakra reservoir, the MAR is projected to increase to 22,974 MCM (mid-century) and 23,589 MCM (end-century) from the baseline MAR of 21,746 MCM. The reason for the relatively modest increase in the runoff is the high evaporation loss that will attend the higher summer temperatures projected for the basin. As indicated in Figure 3b, the mean temperature is projected to increase significantly by between 4.0ºC to 5.0ºC during the summer months, with implications for the evaporative demands.

The WEAP model also suggests a significant reduction in glaciers volume in the study area. The mean annual glaciers volume was estimated to be approximately 1,403 cubic kilometres (km^3) in the baseline period but this is projected to decline to 1,197 km^3 by mid-century (i.e. a reduction by of 14.5%) and to 876 km^3 by the end-century, which represents a whopping reduction of approximately 38%.

Socio-economic projections

Population in the Beas-Sutlej catchment under SSP1 would rapidly increase in the mid-century by 45% relative to the baseline (2000), and thereafter slowing down to a further 15% rise in the end of the century, with implication for the water supply demand although as noted previously any increase will still be expected to be dwarfed by the irrigation water needs.

For land use change projection analyses, selection of appropriate explanatory variables is a crucial step, which in this study are population, terrain elevation and slope, GDP, and distance to cities, rivers, and roads. Based on the Cramer's phi (φ_c)(Cramér 1946) test results, elevation (0.375) and population (0.260) all showed a very strong correlation with the land use change. Slope (0.247), GDP (0.214), and distance to cities (0.199) were also well correlated, while distance to rivers (0.134) showed a moderate correlation. Distance to roads (0.089) was the only factor that exhibited a weak correlation to land use changes. Classification for each explanatory variable is based on the suggestion by Akoglu (2018) (i.e. φ_c > 0.25 is very strong; > 0.15 is strong; > 0.10 is moderate; > 0.05 is weak; and 0 is not meaningful). Potential probability transition matrix predicted using the MLP neural network proved successful with R^2 > 0.83 and RMSE that varied between 0.01 – 0.37 during the training and testing stages, respectively. Additionally, the performance of the Markov Chain simulation of the land use map was very good based on visual comparison of the observed and simulated 2010 map used for model validation as shown in Figure 4. This good performance is supported by the Kapa indices: $K_{standard}$ = 98.42%, K_{no} = 96.02%, $K_{location}$ = 98.13%, $K_{quantity}$ = 96.43%, all of which are very high. The land use projections are shown in Figure 5 and generally reveal rising urbanisation during the century; changes in the other land types are very modest.

Figure 5 is the aggregate picture but there are differences in the situations of the three States. For example, analysing the detailed results suggests that cultivated land requiring irrigation in Punjab will decrease by between 15% and 30% during mid- and end-century respectively primarily due to conversions of agricultural land to urban developments. The corresponding figures in Haryana are 5% and 10% respectively. These reductions in irrigated land will free up water which can go to either relieving the current demand-supply imbalance mentioned earlier, including possible transfers to other States that are currently having water scarcity problem such as the arid and semi-arid Rajasthan. Indeed, irrigated land in Rajasthan is expected to expand by about 12% to 18% in the future compared to the baseline period and additional water resources must be provided to cater for the increased agricultural activities. Although urbanisation at Rajasthan is also increasing, much of the gain of agricultural land in the State has come from the conversion of shrub land to arable land.

Future water demand for irrigation and hydropower production

The WEAP results show that irrigation water demand will reduce by between 8% and 13% at Punjab and by between 1% and 9% at Haryana depending on the time slice, with the higher decrease occurring at end of century (see Figure 6). Rajasthan, on the other hand, showed a rise of between 13% and 14% in irrigation requirements compared to the baseline. These changes agree with the land use changes patterns, with reductions in irrigated land producing less water demand and vice-versa.

The performance indices of the water resources systems in meeting the irrigation water demands are shown in Figure 7. Although all the four indices defined in Eqs 5a-d were evaluated, the discussion here will only focus on the reliability and vulnerability because they are the ones most directly related to water availability. The reduction in irrigated land in Punjab has translated to a much better performance of the water resources systems in satisfying the irrigation demand. In Rajasthan, the reliability of supply would remain essentially unchanged despite the larger area cultivated because of increased water availability due to the reduction of Punjab and Haryana water requirements and the increase in total runoff on average. However, it would experience high vulnerability due to increasing of irrigation water demand as the result of expansion in the cultivated land. Adaptation strategies are thus required in Rajasthan to counter the increased projected vulnerability.

In line with projected future energy requirements, our finding suggests that hydropower production in the system would be sufficient, except for a slight shortage in mid-century due to increasing urban demands under SSP1 projection (see Figure 8). The performance indices in relation to hydropower generation are shown in Figure 9 which reveals a very marked reliability improvement relative to the baseline at Bhakra reservoir. The trend of the vulnerability is also desirable, with this projected to reduce in the future. However, while these improvements in hydropower performance are welcome, it is possible to further enhance performance with the increasing future runoff and the reduction in irrigation water demand by better reservoir operational practices. This can be done by enhancing the available head for hydropower generation in Bhakra and Pong reservoirs through better (optimal) operational practice, which would generate an energy surplus that could be used in other regions. The use of the WEAP model in the work has constrained the way the reservoirs were operated, relying on trial-and-error designed zone-based rule curves and hedging policies. Adeloye et al. (2016) showed that optimised forms of such rule curves and hedging policies not only make the task of operating reservoirs easier, they also enhance the performance especially during low flow situations.

Adaptation strategies for agriculture

The Indian national statistical figures show that the States of Punjab, Haryana and Rajasthan account for more than 50% of the central pool of cereal stocks in the country. In particular, the State of Punjab has played an important role in the success of the Indian "Green Revolution" that introduced not only new agricultural technologies but also high-yielding varieties of wheat and rice (Kohli and Singh 1998). Nevertheless, based on the findings of the study, changes in irrigated land and future runoff situations could significantly influence the future production of these crops if effective adaptive strategies are not implemented that safeguard rural livelihoods and sustainable development.

Adaptation can encompass either changes in large-scale infrastructure (i.e. supply management) or behavioural shifts such as using less water and changing crop practices (i.e. demand management). In line with the narrative of SSP1, this study adopts a demand management approach to reduce the water supply requirements of the largest water demand in the system, i.e. agriculture. In particular, changes in existing cropping patterns were explored in the different command areas of Punjab, Haryana and Rajasthan.

In Punjab, rice and wheat are primary crops with a proportion of cultivated land between rice and wheat in 2000 is approximately 45% and 55%, respectively (ENVIS 2020), which is assumed to be maintained in the future. The average annual production of these crops in the baseline is 9.2 billion kg for rice and 15.5 billion kg for wheat (ENVIS 2020), while the total consumption is estimated to be 8.5 billion kg for rice and 17.8 billion kg for wheat which were derived from the WEAP model. Taking the projected climate and land use changes into account, a deficit for wheat in Punjab of 2.4 billion kg would appear by the end of the century. For rice, although declining in total production in the future, our modelling indicates there would still be a surplus (Figure 10a). A proposed adaptation strategy is to increase the cultivated land for wheat by 10% by reducing rice area by the same 10% in the *Kharif* season. Note that crops that are sown in the pre-monsoon or monsoon (July to October) are called *Kharif* crops, and those that are sown in the winter (October to March) are called *Rabi* crops. The simulated result reveals a significant reduction in the end-Century wheat deficit to 1.7 billion kg, whereas land reduction for rice has not changed its surplus status in future (see dotted lines in Figure 10). It should also be noted that this adaptive option would not increase irrigation water demand because wheat typically consumes less water than rice (note that producing a kilogram of rice requires an average of 2.8 m^3 of water, while a kilogram of wheat takes 1.654 m^3 (WaterAid 2019)); consequently, irrigation water demand might even reduce.

In Haryana, rice and wheat are primary crops, accounting for 79% of the cultivated land (34% for rice and 45% for wheat). Rice and cotton are normally grown during *Kharif* season, but wheat and barley are grown during the *Rabi*. Similar to Punjab, a reduction of 10% of rice area in the *Kharif* on which wheat is planted was simulated and this resulted in drop in wheat deficit to 1.5 billion kg at the end-century (Figure 10b). No change is proposed in the *Rabi* season, where wheat remains the dominant cultivated crops.

In contrast to Punjab and Haryana, Rajasthan expects high irrigation water demand (14%) in the future under the climate and land use projections. Rajasthan is arid (60%) and semi-arid (40%), with low mean annual rainfall between 400 and 800 mm. The main crops are millet which is mainly rainfed and grown during *Kharif* season, and wheat which is grown in the *Rabi*. The percentages of the land devoted to these are roughly 45% and 55%, respectively. Converting 10% wheat land to grow more millet will result in lower irrigation water demand but as shown by the simulation results in Figure 10c, the impact of this adaptive strategy is minimal. Furthermore, both crops will still be in deficit at the end of century. A more effective option is to have a closer look at the allocations to the three riparian states as enshrined in Bhakra Nangal Agreement 1959 (BBMB 1959) and Agreement 1981 implemented in 1982 (Dhillon 1996). According to the 1981 Agreement, total water allocated to Punjab, Haryana, and Rajasthan are 44%, 27%, and 29%, respectively, whereof 57.88%, 32.31%, and 9.81% from the Sutlej river and 30%, 21%, and 49% from the Ravi and Beas rivers (Jain et al. 2007). Given that the Punjab and Haryana are showing reduced irrigation water demands in the future, prioritizing water supply to Rajasthan could increase its available surface water resources by about 15% to 35%, which will go towards meeting the increased irrigation water demands and reduce the pressure on the groundwater abstractions in the State. While this is a hydrologically plausible adaptation strategy, it might not materialize given the political sensitivity associated with water resources issues in the region, and the likelihood is that the respective States will go to any length to guard against anything that might disadvantage them from any tampering with the provisions of existing water allocation Agreements.

Conclusions

The evaluation of the effects of global climate and socio-economic changes on water security in the Sutlej-Beas water resources system in Indian Himalaya, under a high-end climate but sustainable socio-economic scenario, has revealed that higher runoff is likely to occur over the pre-monsoon to monsoon seasons, as consequence of glacier melting associated with rising temperature and the monsoon rainfall. Detailed analyses of land use changes suggest large shifts of irrigation land to urban centres in the downstream States of Punjab and Haryana, whereas the opposite occurred in the State of Rajasthan which has resulted in slight water shortages in water supply for irrigation in Rajasthan. However, the reduction of glaciers and snowmelt coupled with rising population and altered land use/cover could have serious implications for water security beyond the end of the century. Thus, adaptation is necessary for sustaining water resources in the region, mainly to minimise water shortages in Rajasthan and to anticipate water supply challenges in the longer term. Changing crops such as from rice to wheat appears to be an effective option to reduce water requirements while ensuring food security. Further detailed studies on reservoir operation rules could shed more light on potential supply management solutions to enhance water supply for irrigation and hydropower production.

This study shows the importance of accounting for climate, population and land use changes as well as the influence of water infrastructure and policies to understand future water security risks. Only in this way is it possible to develop appropriate adaptation measures that can ensure reliable access to water resources in the future and support sustainable development.

The study is certainly not without its limitations, some of which will be discussed here for the purpose of future work. The application of the delta scaling approach for climate change was justified but it would be necessary to investigate how this approach compares to other approaches in which the climate is downscaled statistically or dynamically. Another aspect is our choice of single GCM, RCP8.5 and SSP1 scenarios for the project. While we have argued that there the complex topographical terrain of the study area does not warrant using a mix of these scenarios, it would still be necessary to see how the other GCMs, RCPs and SSPs do independently, which can then be compared with the specific ones used in this study. Given that these scenarios are projections, developing the full mix of impacts will be valuable for stakeholders involved in making decision of adaptation strategies. Finally, we have provided evidence of the impacts and options for adaptation for decision makers using the WEAP model. With regard to the two major water resources facilities, the Bhakra and Pong reservoirs, we have characterised their projected performance and found them to be largely satisfactory. However, all this assumes that the facilities will be operated according to the default operating policies in WEAP. There is no guarantee that this will be the case and significant departures from the performance might happen as a consequence.

Data Availability Statement

All data generated or used during the study are publically available at https://doi.org/10.4121/uuid:b55e1df0-7dd2-4c25-bb26-54fe1121f7c8 in accordance with funder data retention policies.

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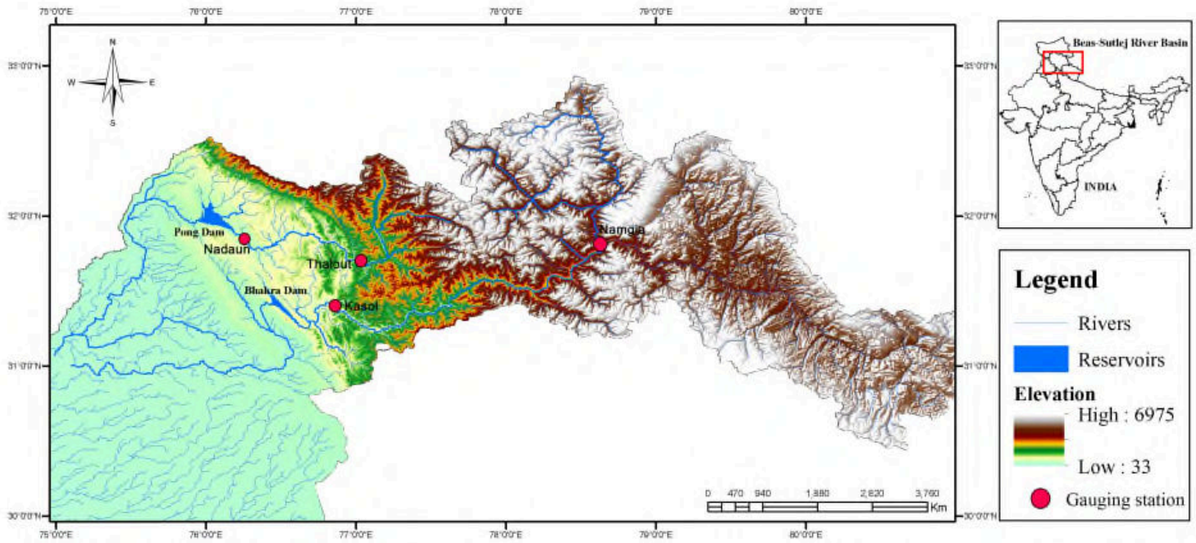

Figure 1. The Beas-Sutlej river basin, India (Source: Data from ASTER Global Digital Elevation Model)

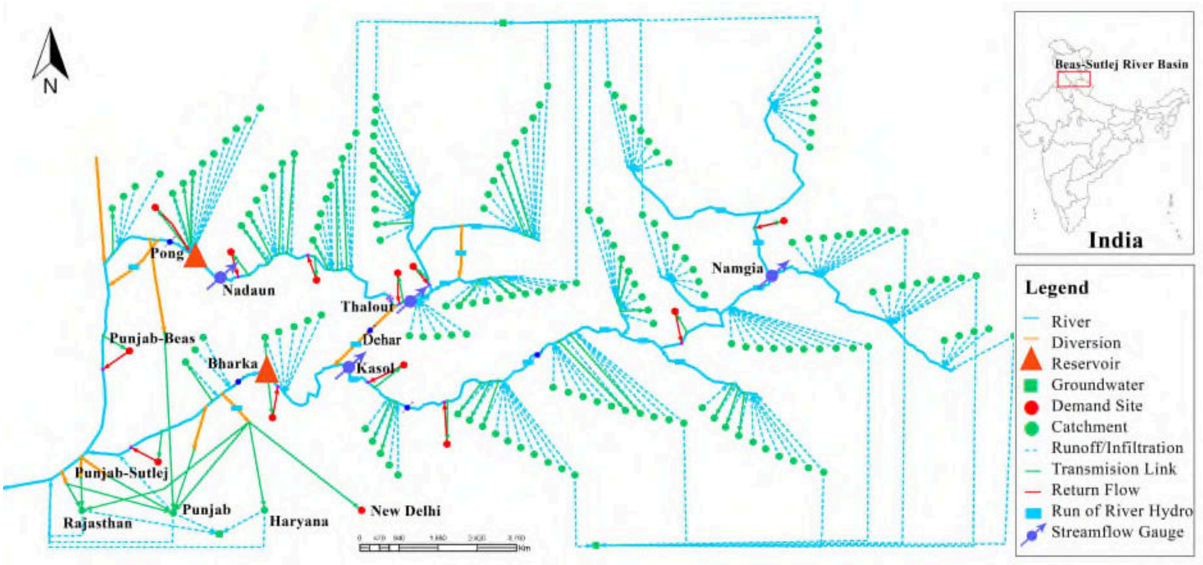

Figure 2. Graphical diagram of the WEAP Sutlej-Beas model.

Figure 3. Mean monthly changes in (a) precipitation and (b) temperature.

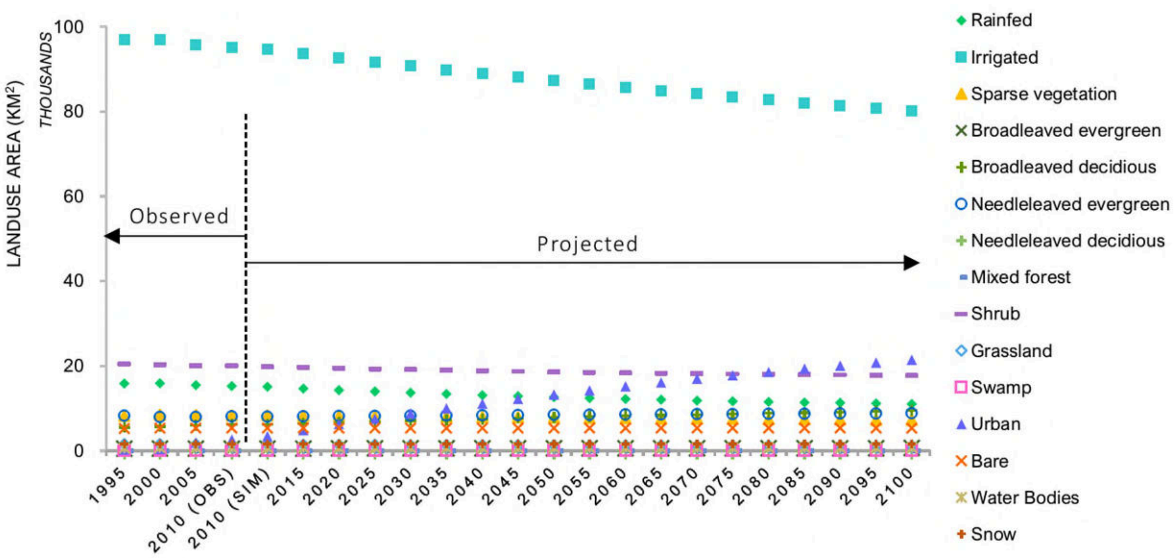

Figure 4. Comparison of land use maps in 2010 between observation and projection

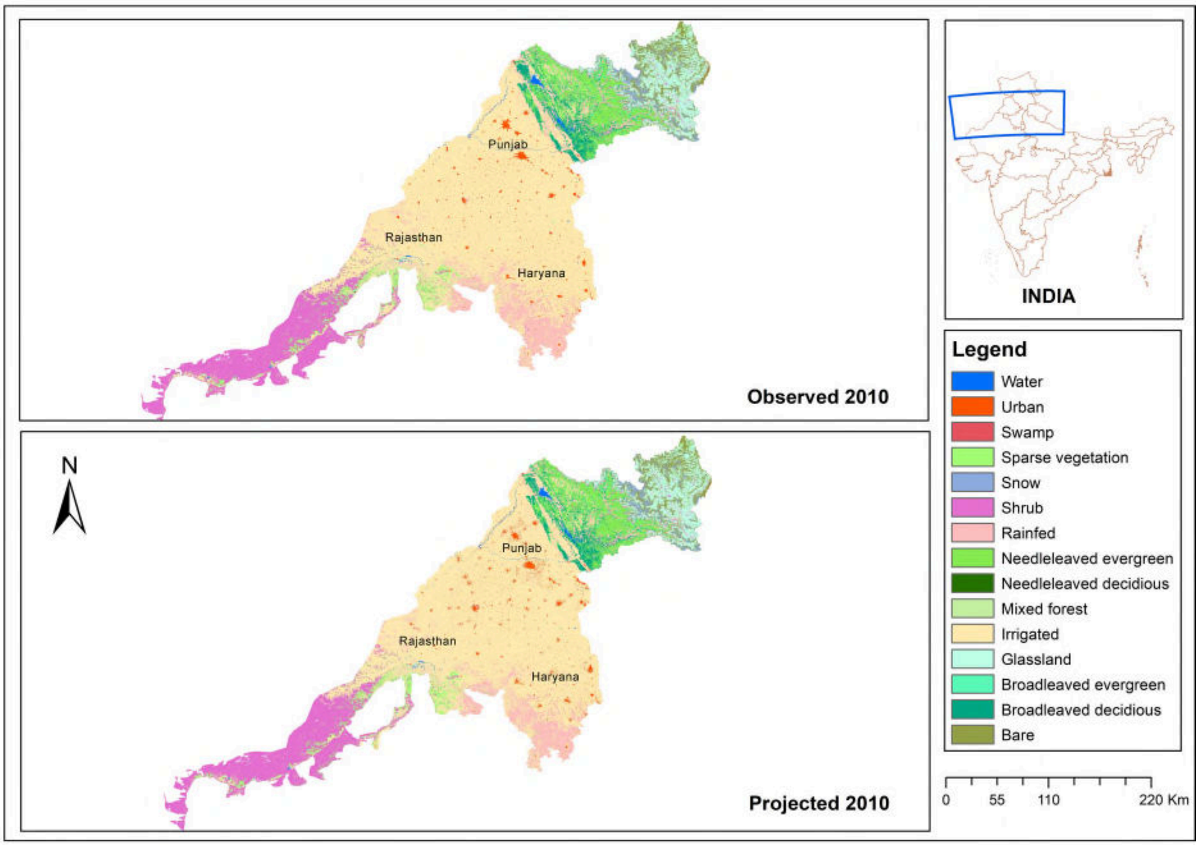

Figure 5. Land use change projection based on Markov Chain approach (Source: Baseline land cover data 2010 from ESA-CCI. Land use projection result data available at https://doi.org/10.4121/uuid:b55e1df0-7dd2-4c25-bb26-54fe1121f7c8)

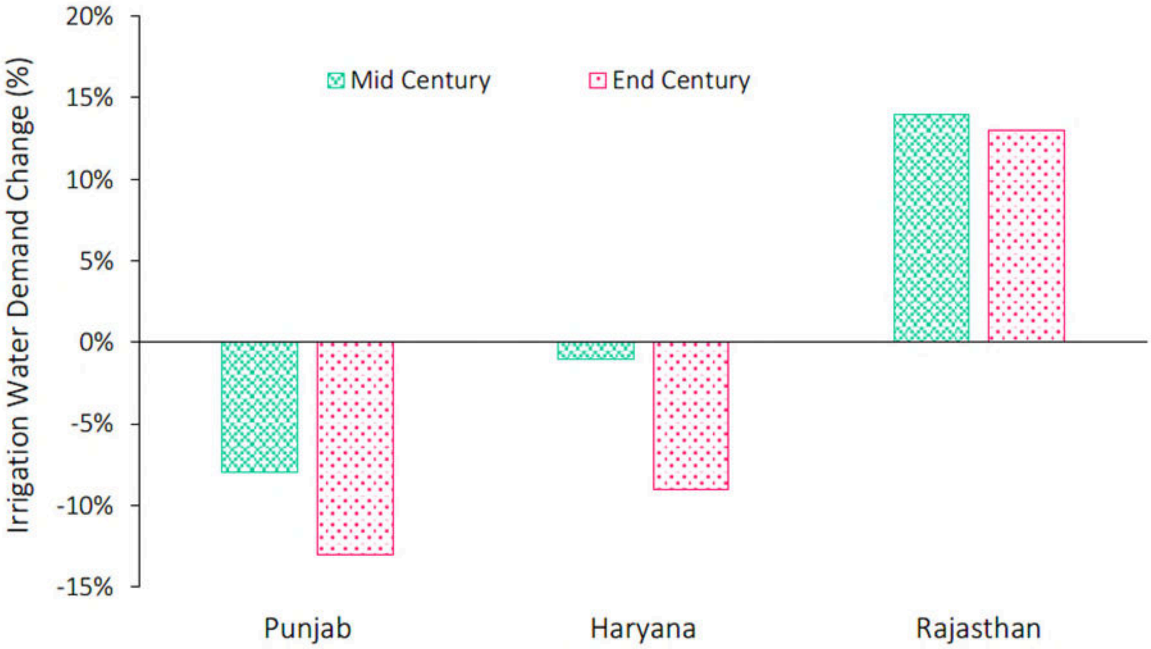

Figure 6. Irrigation water demand changes for mid- and end-century

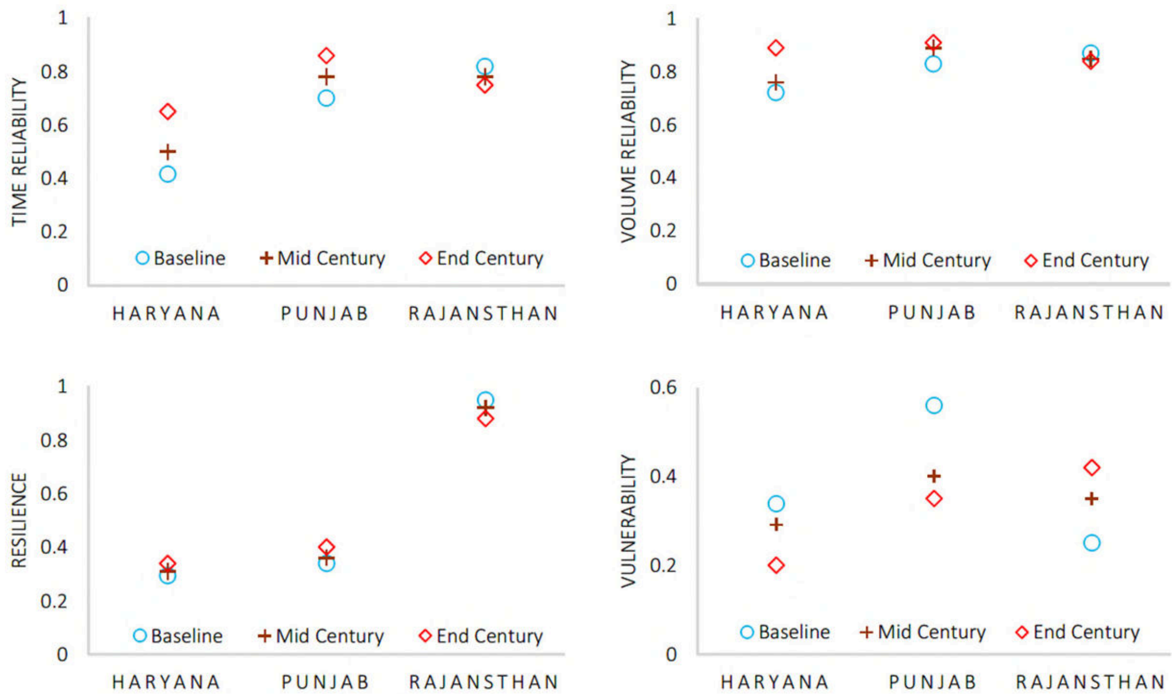

Figure 7. Performance indices for irrigation water demands

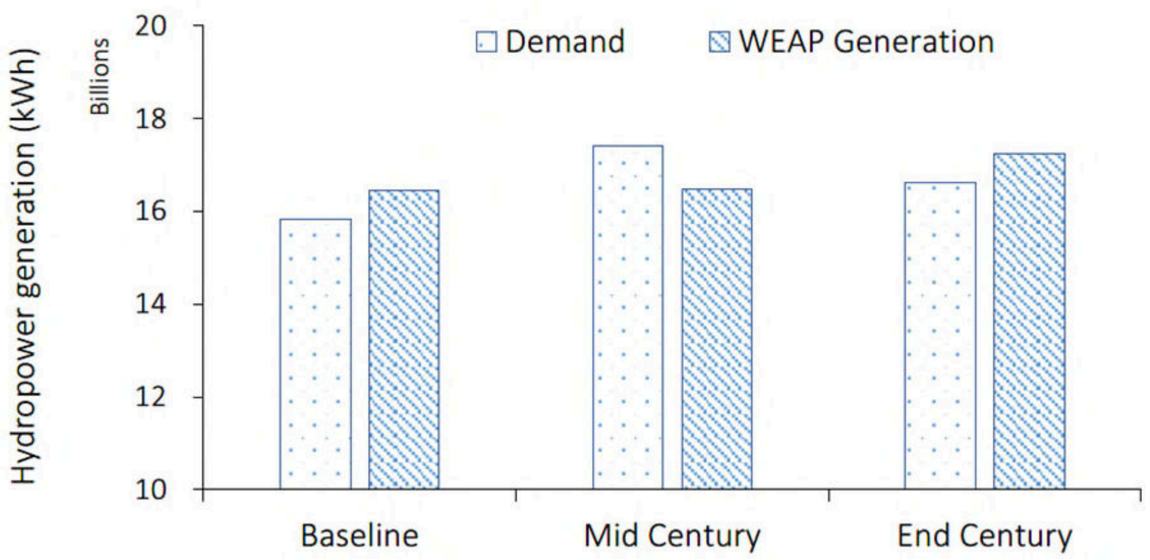

Figure 8. Projected hydropower generation in Beas-Sutlej basin

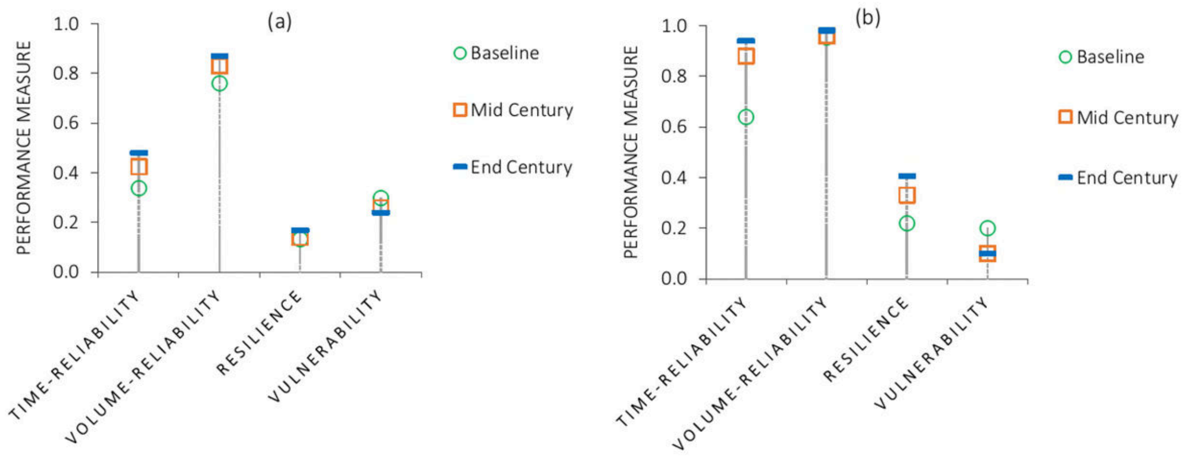

Figure 9. Performance indices for hydropower generation at (a) Pong and (b) Bhakra reservoirs

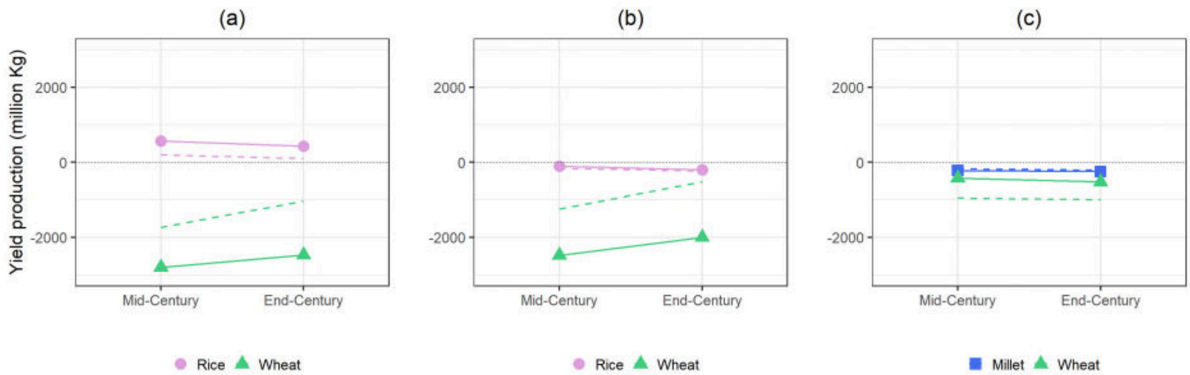

Figure 10. Crops yield response to climate change in (a) Punjab, (b) Haryana, and (c) Rajasthan States without land-use adaptation (solid line) and with land-use adaptation (dotted line)

Table 1. Details of the command areas supplied from Bhakra and Pong reservoirs

State	Irrigation				Domestic Supply		
	Gross irrigation area (million hectares)	Main crops - *Kharif*	Main crops - *Rabi*	Gross water requirement (BCM)	Urban (MCM)	Rural (MCM)	Total (MCM)
Punjab	7.442[a]	Rice, maize, sugarcane, cotton, and pulses	Wheat, gram, barley, potatoes, and winter vegetables	61.5[b]	411	407	818
Haryana	5.446[a]	Sugarcane, wheat, groundnut, maize, and rice	Barley and cotton	17[c]	384	301	685
Rajasthan	8.09[a]	Bajra, pulses, jowar, maize, and groundnut	Barley, wheat, gram, and old seeds	38.85[d]	632	651	1,283

Source: [a]Data from DAC (2018), [b]Data from Kaur et al. (2010), [c]Data from Rawat et al. (2018), and [d]Data from Misra (2017)

Table 2. Calibration and validation results including period, and performance indicators. The location of the four gauging stations is presented in (Momblanch et al. 2019)

Station	Activity	Period	Pearson	Nash-Sutcliffe	% bias
Thalout discharge (MCM/month)	Calibration	1991-1998	0.89	0.74	7.40
	Validation	1999-2005	0.88	0.61	4.50
Jwalamukhi discharge (MCM/month)	Calibration	1991-1999	0.90	0.80	-1.40
	Validation	2000-2007	0.84	0.50	-0.80
Namgia discharge (MCM/month)	Calibration	1991-1998	0.76	0.56	-10.00
	Validation	1999-2004	0.70	0.45	15.00
Kasol discharge (MCM/month)	Calibration	1991-1999	0.89	0.77	-1.05
	Validation	2000-2007	0.84	0.53	11.40
Pong volumes (MCM)	Calibration	1998-2003	0.83	0.68	-0.87
	Validation	2004-2007	0.81	0.55	4.23
Bhakra levels (masl)	Calibration	2000-2004	0.87	0.77	0.10
	Validation	2005-2007	0.84	0.57	-1.00